AMERICAN PSYCHOLOGICAL ASSOCIATION

Emotion

ISSN: 1528-3542

2024, Vol. 24, No. 5, 1149–1156
https://doi.org/10.1037/emo0001341

Trajectories of Affective Well-Being and Survival in Middle-Aged and Older Adults

Dakota W. Cintron[1, 2] and Anthony D. Ong[1, 2]
[1] Department of Psychology, Cornell University
[2] Center for Integrative Developmental Science, Cornell University

Affective experiences are key components of subjective well-being with important implications for health. However, little is known about heterogeneous longitudinal affect trajectories and their links to survival. This study identified joint trajectory subgroups based on 18-year changes in positive affect (PA) and negative affect (NA) and examined their differential associations with mortality risk. Participants were 3,250 adults (aged 39–93 years) from the Midlife in the U.S. study assessed over three waves (1995–2013). Parallel growth mixture modeling revealed three subgroups: (a) improving (increasing PA, decreasing NA), (b) deteriorating (decreasing PA, increasing NA), and (c) flourishing (high, stable PA, low, stable NA). Adjusting for baseline demographic and health covariates, Cox proportional-hazard results showed the improving group had the lowest mortality risk (HR = 0.82, 95% CI [0.35, 1.32]) and the deteriorating group had the highest mortality risk (HR = 1.86, 95% CI [1.34, 3.55]), relative to flourishing. These findings highlight the importance of modeling multidimensional trajectories of affective well-being and their heterogeneous links to survival.

Keywords: positive affect, negative affect, survival, growth mixture modeling

Supplemental materials: https://doi.org/10.1037/emo0001341.supp

Affective experiences are key components of subjective well-being with profound implications for health and longevity (Chida & Steptoe, 2008; DeSteno et al., 2013). In particular, positive affect (PA) and negative affect (NA) represent critical markers of emotional vitality and disturbance, respectively (Ong, 2010; Pressman & Cohen, 2005). Although extensive evidence has linked affective states to life outcomes (Pressman et al., 2019; Steptoe, 2019), less is known about how long term, heterogeneous trajectories of affective well-being relate to mortality. Examining subgroups based on distinct longitudinal patterns of PA and NA can provide nuanced insights into the pathways connecting dynamic emotions and survival over time.

This article was published Online First January 8, 2024.
Dakota W. Cintron https://orcid.org/0000-0002-3869-8243
This research was supported, in part, by Grant P01-AG020166 from the National Institute on Aging to conduct a longitudinal follow-up of the MIDUS (Midlife in the United States) investigation. The original study was supported by the John D. and Catherine T. MacArthur Foundation Research Network on Successful Midlife Development. The data for this study are publicly available online at https://midus.colectica.org/. Analysis code and research materials are available at https://osf.io/waf2m/.

Dakota W. Cintron served as lead for conceptualization, data curation, formal analysis, methodology, visualization, and writing–original draft. Anthony D. Ong served in a supporting role for conceptualization and visualization. Dakota W. Cintron and Anthony D. Ong contributed equally to writing–review and editing.

Correspondence concerning this article should be addressed to Dakota W. Cintron, Department of Psychology, Cornell University, G77 Martha Van Rensselaer Hall, Ithaca, NY 14853-4401, United States. Email: dwc237@cornell.edu

In the current study, we aimed to identify subgroups exhibiting distinct longitudinal patterns of PA and NA states. Our focus was on trajectories of experienced positive and negative emotions rather than the broader constructs of psychological and social flourishing, encompassing facets like purpose in life, close relationships, and social integration (Keyes, 1998, 2007; Ryff & Singer, 2000). We aimed to elucidate the heterogeneous affective pathways linking positive and negative emotional experiences to mortality risk across adulthood. Identifying joint trajectory subgroups defined by shifts in PA and NA can reveal how these core affective components combine to influence well-being and health outcomes over the life course (Cacioppo & Berntson, 1999). This approach moves beyond examining emotional trajectories in isolation to capture the interconnected nature of PA and NA (Reich et al., 2003).

Several theoretical frameworks provide insights into heterogeneous emotional development across adulthood and the need to examine longitudinal affective patterns. For instance, socioemotional selectivity theory (SST; Carstensen et al., 1999) proposes that as time horizons shrink, adults prioritize emotional fulfillment through positive experiences and meaningful relationships. This motivational shift may manifest as improving affective well-being, with older adults selectively engaging in activities that enhance PA and reduce NA. In contrast, strength and vulnerability integration theory (SAVI; Charles, 2010) posits that aging involves a dynamic interplay between emotional strengths (e.g., regulation, positivity) and vulnerabilities (e.g., losses). This framework predicts heterogeneity in affective trajectories, encompassing stability, improvement, or decline depending on contextual factors. Finally, dynamic integration theory (DIT; Labouvie-Vief, 2003) emphasizes negotiating the balance between complexity and intensity of emotions. DIT proposes that negotiating this balance is a key developmental task, implying potential fluctuations in both PA and NA over time as integration and differentiation evolve. Together, these theoretical frameworks point to the dynamic nature of affect and the need to examine heterogeneous trajectories, which may show stability, improvement, or variability in emotional well-being.

Affective Well-Being Trajectories

Although prior studies have examined PA or NA trajectories, few have modeled their dynamic co-occurrence. For instance, Zaninotto et al. (2016) showed that sustained enjoyment of life over time predicted longer survival, while Willroth et al. (2020) found that increases in PA uniquely predicted better health. While these studies offer insights into the relationships between specific affective components and health, there remains a need for more comprehensive investigations into individual variations in affective well-being trajectories over time. Modeling the dynamic co-occurrence of PA and NA may reveal critical information about their interconnected nature and combined influence on outcomes (Cacioppo & Berntson, 1999; Reich et al., 2003). Identifying subgroups based on distinct joint trajectories can provide targeted insights into the multifaceted affective pathways that shape well-being and health over time (Keyes, 2007; Ryff et al., 1998).

Joint Modeling of PA and NA

Person-centered approaches are well-suited for identifying distinct trajectory subgroups (Busseri et al., 2009; Howard & Hoffman, 2018; Laursen & Hoff, 2006; Nagin & Tremblay, 2005). These subgroups reflect variations in trajectories of affective well-being. Some individuals exhibit patterns of maintaining or improving affective well-being over time, while others may exhibit patterns of declining affective well-being. Recognizing these diverse subgroups can inform targeted interventions to promote positive emotional states and mitigate the potential adverse health effects arising from poor affective well-being.

Recent studies reveal subgroups showing stable, increasing, or decreasing well-being trajectories relate differentially to health outcomes (Guimond et al., 2022; Lim et al., 2017; Radler et al., 2018). Notably, these studies focused on psychological and evaluative well-being (e.g., purpose in life, life satisfaction), and it remains unclear whether longitudinal trajectories of affective well-being demonstrate similar protective associations. Focusing on affective well-being trajectories provides insights into the dynamic interplay between PA and NA, enhancing understanding of the multifaceted nature of affective well-being and its implications for overall health. Moreover, unlike previous studies modeling PA and NA separately using growth curve modeling (Willroth et al., 2020) or psychological well-being facets separately using latent class growth modeling (Guimond et al., 2022; Nagin & Tremblay, 2005), we use parallel growth mixture modeling (Muthén & Muthén, 1998–2017; Ram & Grimm, 2009; Wickrama et al., 2021) to examine the combined influence of heterogeneous PA and NA trajectories on survival. This joint modeling approach assesses how combinations of heterogeneous PA and NA trajectories influence survival, elucidating their interconnected nature.

Affective Well-Being and Mortality

Affective well-being shows established connections to physical health and survival (Chida & Steptoe, 2008; Pressman & Cohen, 2005). Although some evidence links high, stable PA to lower mortality (Willroth et al., 2020; Zaninotto et al., 2016), heterogeneity in these associations remains underexplored. Examining joint trajectories of PA and NA can elucidate multidimensional pathways linking emotions and survival. For instance, stable high PA and low NA may reflect affective pathways associated with survival benefits, whereas declining PA and rising NA may reflect affective patterns associated with greater mortality risk.

Theoretical explanations for the ties between affective well-being and mortality posit that high PA may benefit physiological functioning through improved immune and cardiovascular systems, while high NA can dysregulate these systems through autonomic, neuroendocrine, and inflammatory pathways (Boehm & Kubzansky, 2012; Pressman & Cohen, 2005). Empirically, high PA has been associated with lower cortisol output, reduced cardiovascular disease risk, and heightened antibody response, whereas high NA is linked to elevated inflammation and poorer cardiovascular health (see Steptoe et al., 2005, 2007). Such effects are believed to cumulatively influence morbidity and mortality over the long term.

The Current Study

This study examined the association between latent trajectories of PA and NA and mortality risk in a large sample of U.S. adults. We used measures of PA and NA assessed three times over 18 years and analyzed associations with mortality in a large, national sample of older men and women from the Midlife in the United States (MIDUS) study. Building on prior theoretical frameworks (Carstensen et al., 1999; Charles, 2010; Labouvie-Vief, 2003) and empirical studies (Guimond et al., 2022; Lim et al., 2017; Radler et al., 2018), we defined flourishing trajectories as maintaining relatively high, stable levels of PA and low, stable levels of NA over time. Deteriorating trajectories were conceptualized as exhibiting marked declines in PA and increases in NA over the follow-up period. Finally, improving trajectories were characterized by showing increasing PA and decreasing NA over time.

We hypothesized that adults exhibiting flourishing trajectories would have the greatest survival over the follow-up period, as they may benefit from both the protective effects of PA and the absence of harmful effects of NA. Conversely, those with deteriorating trajectories were expected to show the highest mortality risk, as they may suffer from both the lack of protective effects of PA and the presence of harmful effects of NA. Adults with improving trajectories were expected to show intermediate survival compared to flourishing and deteriorating subgroups, reflecting gradual gains in PA's beneficial effects and reductions in NA's adverse influences.

Method

Study Population

Data for this study were drawn from the MIDUS study. The MIDUS cohort is a national longitudinal sample of U.S. adults (N = 7,108; age = 24–74 years) recruited from 1995 to 1996 (MIDUS 1). Participants from MIDUS 1 were reinvited for follow-up assessments in 2004–2006 (MIDUS 2) and 2013–2015 (MIDUS 3). The current analyses used data from MIDUS participants (N = 3,250; age = 39–93 years) who completed assessments at all three waves and did not have complete missing data on the PA and NA measures. Data collection for the MIDUS studies was approved by the Institutional Review Boards at each participating site, and all participants provided informed consent.

Measures

Affective Well-Being

Participants were asked to rate how much during the past 30 days they felt each of six PA items (cheerful, in good spirits, extremely happy, calm and peaceful, satisfied, and full of life) and six NA items (so sad nothing could cheer you up, nervous, restless, nervous, everything was an effort, and worthless). Item responses were Likert-scaled and ranged from 1 (*all of the time*) to 5 (*none of the time*). We reverse-coded PA and NA items such that higher PA scale scores indicated greater PA and higher NA scale scores indicated greater NA. Across the three waves, Cronbach's αs ranged from .90 to .91. Prior research indicates that these PA and NA measures have evidence of strong psychometric properties, including strong (scalar) invariance across age and gender groups and over time (Chan et al., 2020; Joshanloo & Bakhshi, 2016; Mroczek & Kolarz, 1998).

Mortality and Survival

Data on mortality were collected using three methods: (a) National Death Index reports conducted in 2006, 2009, and 2016; (b) tracing and mortality closeout interviews conducted by the University of Wisconsin Survey Center as part of MIDUS 3 (2013–2015); and (c) deaths recorded during regular longitudinal sample maintenance through 2021. Survival time in months was calculated by subtracting January 1, 2013 (beginning of MIDUS Wave 3 data collection) from the month and year of death.

Demographic Covariates

Chronological age in years was computed by subtracting birthdates from the baseline interview date. Self-reported sex (male or female), employment (currently working or not), race (non-White or White), and marital status (married or not) were collected at baseline. Income at baseline was assessed from household total income from wage, pension, social security, and other sources. We log-transformed income to account for positive skew. Education at baseline was assessed on a 12-point scale ranging from 1 (*no school/some grade school*) to 12 (*PhD, MD, JD, or other professional degree*).

Health Covariates

Self-reported general health was collected at baseline with the question, "Using a scale from 0 to 10 where 0 means 'the worst possible health' and 10 means 'the best possible health,' how would you rate your health these days?" The number of self-reported chronic health conditions in the past 12 months was collected at baseline. Body mass index (BMI) at baseline was calculated by dividing the respondent's weight (mass) in kilograms by heights in meters squared. Basic difficulties with activities of daily living (ADL) at baseline were measured using a scale constructed from seven items asking, "How much does your health limit you in doing each of the following?" and include, for example, "lifting or carrying groceries," "bending, kneeling, or stooping," and "walking several blocks."

Statistical Analysis

Analyses proceeded in three steps. To identify multiple trajectory subgroups, we first used latent growth curve modeling (McCoach & Cintron, 2022) to estimate the overall trajectory of PA and NA over 18 years. We fit three unconditional latent growth models for PA and NA (i.e., without covariates): an intercept-only model, a linear model, and a quadratic model. A linear trajectory for both PA and NA was selected based on the Bayesian information criterion (BIC; Schwarz, 1978).

Second, based on results from the first step, we used parallel growth mixture modeling (Muthén & Muthén, 1998–2017; Ram & Grimm, 2009; Wickrama et al., 2021) to identify subgroups of adults with distinct PA and NA joint trajectories. This approach fits a mixture model to the PA and NA growth trajectories where each resultant joint trajectory combines a trajectory for PA and a trajectory for NA (see Figure S1 in the online supplemental materials). To handle missing data in the PA and NA measures during class enumeration, we used a full-information maximum likelihood estimator in Mplus Version 8.8 with robust standard errors under the missing at-random assumption (Enders & Bandalos, 2001; Muthén & Muthén, 1998–2017).

Several indicators were used to select the optimal number of joint trajectory subgroups: (a) entropy index, (b) BIC, (c) sample size adjusted BIC (aBIC), (d) the bootstrapped likelihood ratio test (BLRT), and (e) the Vuong–Lo–Mendell–Rubin (VLMR) likelihood ratio test. Higher entropy values indicate better class separation. Lower BIC and aBIC values indicate better model fit. Significant BLRT or VLMR p values ($p < .05$) suggest the k-class model fits better than the $k-1$-class model (Nylund et al., 2007; Tein et al., 2013). As growth mixture modeling is exploratory, our model selection procedures involved balancing statistical fit, parsimony, stability, and substantive utility (Grimm et al., 2016; Weiss et al., 2023; Wickrama et al., 2021). The goal was to identify the optimal number of classes that best described the data while balancing complexity, generalizability, and meaningfulness. Models with higher entropy were preferred as prior research indicates the importance of entropy for correct class assignment, with greater entropy corresponding to less overlap between latent classes and better correct class assignment (Cintron et al., 2023). Likewise, more parsimonious models satisfying the selection criteria were preferred, with priority given to the VLMR and BLRT tests given it is not uncommon for information indices (i.e., aBIC/BIC) to decrease for each additional class added (i.e., there is not a global minimum; Nylund-Gibson & Choi, 2018). When fitting the models, the NA slope variance was constrained to zero, and factor/residual variances were held equal across classes to aid convergence and obtain admissible solutions, as is common in practice (Diallo et al., 2016; Kooken et al., 2019; McNeish et al., 2023). Overall, the class enumeration process aimed to select the most appropriate model that provided meaningful insights into heterogeneous affective well-being trajectories.

Third, after identifying joint trajectory subgroups, Cox proportional-hazard models (Asparouhov et al., 2006) evaluated the association between group membership and survival time, before and after adjustment for baseline demographics (i.e., age, gender, race, employment status, marital status, education, income) and health (self-rated health, chronic conditions, BMI, ADL difficulties; see Figure S1 in the online supplemental materials). The profile likelihood method in Mplus 8.8 was used for model estimation (Asparouhov et al., 2006). Survival time was right censored for participants who were still living after December 2021. Bias-adjusted three-step procedures estimated the association between latent class growth trajectories and survival time (Bakk et al., 2013; Vermunt, 2010).

Two sensitivity analyses were conducted. First, parallel censored and censored-inflated growth mixture models evaluated potential floor effects of NA on class enumeration. Second, analyses excluding deaths within 12 and 24 months of the final affect measurement were performed to check for reverse causality (Steptoe, 2019), where declining well-being may reflect approaching end of life. These analyses provided checks to ensure the identified trajectories reflected long-term affective well-being patterns rather than artifacts of floor effects or imminent mortality.

Transparency and Openness

We report how sample size was determined, all data exclusions, manipulations, and measures per JARS guidelines (Kazak, 2018). Study data are publicly available online at https://midus.colectica.org/. Analysis code and materials are available at https://osf.io/waf2m/?view_only=a32ddb5fa21543d1a8a966643e51e1c0 (Cintron & Ong, 2023). The study design and analysis were not preregistered.

Results

Descriptive Statistics

Table 1 summarizes sample demographics, descriptive statistics for key variables, mortality rate, and average survival time in months. PA and NA scores spanned the full 1–5 range. Of the 3,250 participants, 428 (13%) died over the follow-up period. The average survival time was 101 months. Details on the full versus analytic sample can be found in Table S1 in the online supplemental materials.

Parallel Growth Mixture Modeling

Parallel growth mixture models estimating 1–10 classes were fitted. Model fit information is reported in Table 2. A three-class solution was selected based on the VLMR test, high Entropy, and substantive interpretability of the classes. Figure 1 displays the estimated unconditional three-class growth trajectories: (a) improving (7.7%, $n = 214$); (b) deteriorating (9.1%, $n = 231$), and (c) flourishing (83.1%, $n = 2{,}667$).

Table 3 (Panel A) and Figure 1 summarize the three-class growth model. The improving subgroup exhibited moderate levels of PA (intercept = 2.40, $p < .01$) and NA (intercept = 2.84, $p < .01$) at baseline, with large increases in PA (slope = 0.39, $p < .01$) and decreases in NA (slope = −0.58, $p < .01$) over time. The deteriorating subgroup displayed moderate initial levels of PA (intercept = 3.21, $p < .01$) and NA (intercept = 1.73, $p < .01$), with marked decreases in PA (slope = −0.34, $p < .01$) and increases in NA (slope = 0.54, $p < .01$) over time. Finally, the flourishing subgroup showed high levels of PA (intercept = 3.53, $p < .01$) and low levels of NA (intercept = 1.36, $p < .01$) at baseline and relatively stable patterns of PA (slope = 0.01, $p < .11$) and NA (slope = −0.03, $p < .01$) over time.

Table 1
Descriptive Statistics

Data	Count/*M* (percentage/*SD*)
N	3,250
Female	1,792 (55.14)
Age	45.67 (11.40)
Non-White	209 (7.00)
Education	7.31 (2.44)
Not employed	1,040 (32.13)
Married	2,357 (72.52)
Income (log)	10.85 (1.60)
Self-rated health	7.60 (1.47)
Number of chronic conditions	2.22 (2.29)
Body mass index	26.57 (5.11)
Difficulty with ADL	1.45 (0.64)
Time 1 positive affect	3.41 (0.70)
Time 2 positive affect	3.45 (0.69)
Time 3 positive affect	3.43 (0.72)
Time 1 negative affect	1.51 (0.58)
Time 2 negative affect	1.48 (0.54)
Time 3 negative affect	1.47 (0.58)
Mortality (deaths)	428 (13.0)
Survival (months)	101.10 (20.13)

Note. All covariates were measured at MIDUS Wave 1 (i.e., baseline). ADL = activities of daily living; MIDUS = Midlife in the United States.

Survival Analysis

Hazard ratios (HRs) from the Cox models indicate relative mortality risk between affective well-being trajectories where the flourishing subgroup is the reference group. For example, the HR of 1.65 below signifies that the deteriorating group has approximately a 65% greater risk of experiencing mortality compared to the flourishing group. Confidence intervals provide information on estimate precision and uncertainty. Narrower confidence intervals indicate more precise estimates, while wider intervals reflect greater uncertainty. Table 3 (Panel B) shows Cox regression results. Unadjusted HRs were 0.78 (95% CI [0.52, 1.16]) for improving and 1.65 (95% CI [1.24, 2.18]) for deteriorating subgroups relative to the flourishing subgroup. Adjusting for baseline demographics and health, HRs were 0.82 (95% CI [0.35, 1.32]) and 1.86 (95% CI [1.34, 3.55]), respectively. Although survival rates did not significantly differ between improving and flourishing subgroups, the flourishing and improving subgroups had significantly higher odds of survival compared to the deteriorating subgroups. The unadjusted Kaplan–Meier curves in Figure 2 depict 108-month survival probabilities, with the improving subgroup having the highest and the deteriorating subgroup having the lowest probability of survival over follow-up.

Table S2 in the online supplemental materials displays the effects of demographics and baseline health on latent class membership. Older, married adults in better health were more likely to be in flourishing versus improving subgroups. Additionally, those who were older, more educated, and had higher income were more likely to be in the flourishing rather than the deteriorating subgroup. Income was the only predictor distinguishing improving and deteriorating subgroups, with higher incomes among those in the improving subgroup. Importantly, controlling for differential effects of the covariates did not substantively alter the survival analysis results.

Sensitivity Analyses

A sensitivity analysis evaluated potential floor effects on class enumeration by comparing the initial analysis to parallel censored and censored-inflated growth mixture models. The goal was to assess whether the identified subgroups substantially differed across approaches, particularly for NA where floor effects may be present. The improving, deteriorating, and flourishing classes

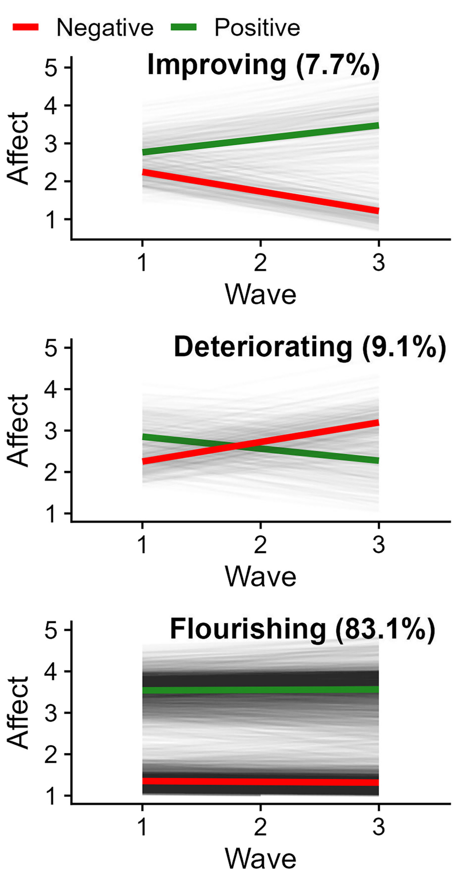
Table 2
Model Fit Indices of Unconditional Parallel Process Growth Mixture Models

Classes	Parameters	LL	Entropy	BIC	aBIC	BLRT	VLMR
1	16	−14,187	—	28,543	28,453	—	—
2	21	−13,625	0.91	27,420	27,353	<.01	<.01
3	26	−13,092	0.91	26,394	26,312	<.01	<.01
4	31	−12,910	0.92	26,071	25,972	<.01	0.10
5	36	−12,759	0.90	25,810	25,695	<.01	0.60
6	41	−12,622	0.90	25,576	25,446	<.01	0.20
7	46	−12,518	0.91	25,408	25,262	<.01	0.10
8	51	−12,445	0.90	25,302	25,140	<.01	0.50
9	56	−12,367	0.89	25,187	25,009	<.01	0.20
10	61	−12,290	0.88	25,073	24,879	<.01	0.20

Note. The choice for three classes was based on the VLMR. LL = log-likelihood; BIC = Bayesian information criterion; aBIC = sample size adjusted BIC; BLRT = bootstrapped likelihood ratio test p value; VLMR = Vuong–Lo–Mendell–Rubin adjusted likelihood ratio test p value.

were consistently replicated across the initial and censored models (Tables S3–S6 in the online supplemental materials), indicating the robustness of these substantive trajectories. However, the censored models also resulted in extraneous subclasses overextracting the flourishing and improving subgroups (Tables S4 and S6 in the online supplemental materials). Since the key classes were stable, the initial three-class solution was retained for survival analysis, suggesting floor effects did not meaningfully impact enumeration. A second sensitivity analysis omitted deaths within 12 ($n = 17$) and 24 ($n = 73$) months of the final assessment to test reverse causation. Associations between joint trajectories and mortality remained unchanged (Tables S7 and S8 in the online supplemental materials), further demonstrating robustness.

Figure 1
Latent Growth Trajectory Classes of Affective Well-Being



Note. See the online article for the color version of this figure.

Discussion

Affective states are key components of subjective well-being and play an important role in the maintenance of health. Little is known, however, about the heterogeneous pathways by which affective well-being and survival are linked over the life course. To our knowledge, this is the first study to (a) describe joint trajectory subgroups of PA and NA across adulthood and (b) examine the relationship between joint trajectory subgroups and mortality. The results revealed three primary multidimensional trajectories over 18 years: improving (increasing PA and decreasing NA), deteriorating (declining PA and rising NA), and flourishing (stable high PA and stable low NA).

Our identification of flourishing, deteriorating, and improving affective trajectories provides nuanced insights that align with theoretical perspectives on emotional aging. Consistent with past research on psychological well-being (Guimond et al., 2022; Lim et al., 2017; Radler et al., 2018), the flourishing pattern marked by sustained high PA and low NA was most prevalent. The stability of high PA and low NA in this subgroup reflects continued emotional regulatory strengths associated with lower mortality risk. However, distinct deteriorating and improving subgroups also emerged, elucidating heterogeneous affective pathways. The improving trajectory, characterized by increasing PA and decreasing NA over time, aligns with SST (Carstensen et al., 1999). This motivational shift toward meaningful emotional experiences in later life was associated with reduced mortality risk, suggesting potential health benefits. In contrast, the deteriorating trajectory exhibited marked declines in PA and rises in NA, denoting failures to achieve emotional goals with advancing age. This subgroup had the highest mortality risk, indicating adverse health impacts.

Together, the flourishing, deteriorating, and improving patterns reveal nuanced interplay between diverse affective pathways and

Table 3
Growth Mixture Model and Survival Analysis Results

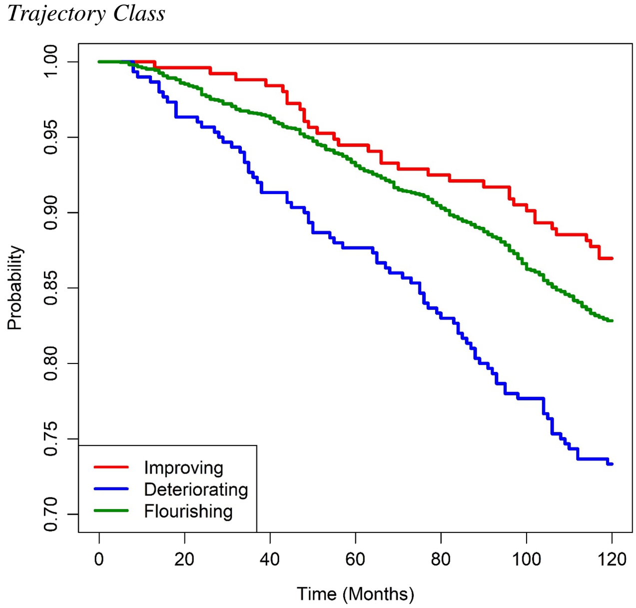
Growth mixture model	Intercept	*SE*	*p*	Slope	*SE*	*p*
Panel A: parallel growth mixture model						
Positive affect						
Class 1 (improving)	2.40	0.05	<.01	0.39	0.04	<.01
Class 2 (deteriorating)	3.21	0.06	<.01	−0.34	0.05	<.01
Class 3 (flourishing)	3.53	0.02	<.01	0.01	0.01	.11
Negative affect						
Class 1 (improving)	2.84	0.08	<.01	−0.58	0.04	<.01
Class 2 (deteriorating)	1.73	0.05	<.01	0.54	0.04	<.01
Class 3 (flourishing)	1.36	0.01	<.01	−0.03	0.01	<.01

	Unadjusted ($N = 3{,}250$)		Demographic ($N = 3{,}082$)		Baseline Health ($N = 2{,}968$)	
Survival Analysis	Coefficient	Hazard ratio [95% CI]	Coefficient	Hazard ratio [95% CI]	Coefficient	Hazard ratio [95% CI]
Panel B: cox proportional-hazard regression models						
Class 1 (improving)	−0.25	0.78 [0.52, 1.16]	0.15	1.17 [0.75, 1.80]	−0.21	0.82 [0.35, 1.32]
Class 2 (deteriorating)	0.50	1.65 [1.24, 2.18]	0.79	2.21 [1.42, 3.42]	0.62	1.86 [1.34, 3.55]
Age			0.11	1.11 [1.10, 1.13]	0.11	1.11 [1.10, 1.13]
Female			−0.38	0.68 [0.57, 0.82]	−0.42	0.66 [0.54, 0.80]
Not currently employed			0.07	1.07 [0.88, 1.30]	−0.01	0.99 [0.81, 1.22]
Married			−0.10	0.91 [0.73, 1.12]	−0.06	0.95 [0.76, 1.17]
Income (log)			−0.02	0.98 [0.94, 1.02]	−0.03	0.98 [0.93, 1.02]
Education			−0.05	0.95 [0.92, 0.99]	−0.04	0.96 [0.93, 1.00]
Non-White			−0.25	0.78 [0.51, 1.19]	−0.22	0.80 [0.52, 1.22]
Self-rated health					−0.05	0.95 [0.89, 1.03]
Number chronic conditions					0.01	1.01 [0.97, 1.06]
Body mass index					0.03	1.03 [1.01, 1.05]
Difficulty ADL					0.27	1.31 [1.13, 1.52]

Note. The reference group in Panel B is the flourishing class; all covariates were measured at MIDUS Wave 1. The effects of the covariates on the latent classes are reported in Table S2 in the online supplemental materials. CI = confidence interval; ADL = activities of daily living; MIDUS = Midlife in the United States.

longevity. Our findings provide empirical insights that align with the SAVI model's premise of heterogeneous affective trajectories differentially linked to survival (Charles, 2010). These trajectories suggest aging involves a dynamic interplay of regulatory strengths, vulnerabilities, and motivational shifts influencing emotional health.

Figure 2
Estimated Kaplan–Meier Survival Curves by Latent Growth Trajectory Class



Note. See the online article for the color version of this figure.

Critically, while overall affective trajectories show ties to mortality (Willroth et al., 2020; Zaninotto et al., 2016), identifying multiple subgroups informs targeted interventions. Our joint trajectory analysis suggests that adults in the deteriorating subgroup were significantly more likely to die over the follow-up period. For these adults, interventions aiming to promote PA and reduce NA over time may be warranted. By comparison, adults whose trajectories reflected marked increases (improving subgroup) or persistently high (flourishing subgroup) affective well-being may benefit from interventions that sustain these favorable patterns over time (Keyes, 2007; Zaninotto et al., 2016).

Limitations and Future Research

This is an observational study, so issues of selection bias, confounding, or reverse causality may limit our ability to draw causal conclusions. For instance, it is known that there is selection bias in who returns in longitudinal studies. However, the full sample and analytic samples showed comparable demographics, health characteristics, and PA and NA at baseline (see Table S1 in the online supplemental materials). Moreover, we adjusted for several potential confounders, including demographic variables and baseline health to protect against these issues. Since later health issues could explain decreasing PA and increasing NA, reverse causality is possible. However, associations were maintained when excluding deaths within 1–2 years of the final affect assessment, arguing against terminal decline effects.

Several modeling constraints should be noted. The three-wave design precluded identifying complex nonlinear patterns, restricting generalizability (Ram & Grimm, 2009). Additional assessment waves could enable more reliable detection of unobserved heterogeneity. Constraining residual variances and fixing the NA slope variance addressed convergence issues but restricted full parameterization (Bauer & Curran, 2003; Diallo et al., 2016). While sensitivity analyses indicated the classes were reasonably robust to floor effects, future research could apply joint covariance pattern mixture models (McNeish et al., 2023). Replication with larger subgroups is important given the small sample sizes in some subgroups (Cintron et al., 2023).

Looking ahead, elucidating contextual influences on affective trajectories represents a critical goal, as does exploring moderators of the affect-health linkage (Carstensen et al., 1999; Charles, 2010). Analyses of interaction effects between PA and NA may offer additional insights into their interconnected nature (Cacioppo & Berntson, 1999; Reich et al., 2003). Assessing nonlinear change and dynamic features like fluctuations and covariation warrants investigation with intensive longitudinal data (Ram & Grimm, 2009). Such research can enhance understanding of the multifaceted, dynamic pathways linking affective well-being and longevity.

Conclusions

This study demonstrates that maintained and enhanced trajectories of affective well-being, encompassing PA and NA, are tied to greater survival in older adults. The results underscore the utility of modeling multidimensional affective patterns over time in relation to longevity (Ong & Steptoe, 2020; Zaninotto et al., 2016). Jointly assessing shifts in PA and NA provided insights into their interconnected influences on mortality risk. Overall, the findings reveal heterogeneous pathways linking dynamic affective states to survival, aligned with theoretical perspectives on socioemotional aging (Carstensen et al., 1999; Charles, 2010). Deteriorating affective trajectories marked by declining PA and rising NA carried the highest mortality risk and may warrant targeted intervention. In contrast, improving and flourishing trajectories signaled more adaptive patterns tied to lower mortality. This research highlights the value of applying person-centered analytical techniques to elucidate multidimensional affective pathways related to health outcomes.

References

Asparouhov, T., Masyn, K., & Muthen, B. (2006, August 6–10). *Continuous time survival in latent variable models*. Proceedings of the Joint Statistical Meetings, Seattle, WA, United States (pp. 180–187).

Bakk, Z., Tekle, F. B., & Vermunt, J. K. (2013). Estimating the association between latent class membership and external variables using bias-adjusted three-step approaches. *Sociological Methodology*, *43*(1), 272–311. https://doi.org/10.1177/0081175012470644

Bauer, D. J., & Curran, P. J. (2003). Distributional assumptions of growth mixture models: Implications for overextraction of latent trajectory classes. *Psychological Methods*, *8*(3), 338–363. https://doi.org/10.1037/1082-989X.8.3.338

Boehm, J. K., & Kubzansky, L. D. (2012). The heart's content: The association between positive psychological well-being and cardiovascular health. *Psychological Bulletin*, *138*(4), 655–691. https://doi.org/10.1037/a0027448

Busseri, M. A., Sadava, S., Molnar, D., & DeCourville, N. (2009). A person-centered approach to subjective well-being. *Journal of Happiness Studies*, *10*(2), 161–181. https://doi.org/10.1007/s10902-007-9072-3

Cacioppo, J. T., & Berntson, G. G. (1999). The affect system: Architecture and operating characteristics. *Current Directions in Psychological Science*, *8*(5), 133–137. https://doi.org/10.1111/1467-8721.00031

Carstensen, L. L., Isaacowitz, D. M., & Charles, S. T. (1999). Taking time seriously: A theory of socioemotional selectivity. *American Psychologist*, *54*(3), 165–181. https://doi.org/10.1037/0003-066X.54.3.165

Chan, M. H., Gerhardt, M., & Feng, X. (2020). Measurement invariance across age groups and over 20 years' time of the negative and positive affect scale (NAPAS). *European Journal of Psychological Assessment*, *36*(4), 537–544. https://doi.org/10.1027/1015-5759/a000529

Charles, S. T. (2010). Strength and vulnerability integration: A model of emotional well-being across adulthood. *Psychological Bulletin*, *136*(6), 1068–1091. https://doi.org/10.1037/a0021232

Chida, Y., & Steptoe, A. (2008). Positive psychological well-being and mortality: A quantitative review of prospective observational studies. *Psychosomatic Medicine*, *70*(7), 741–756. https://doi.org/10.1097/PSY.0b013e31818105ba

Cintron, D. W., Loken, E., & McCoach, D. B. (2023). A cautionary note about having the right mixture model but classifying the wrong people. *Multivariate Behavioral Research*, *58*(4), 675–686. https://doi.org/10.1080/00273171.2022.2082913

Cintron, D. W., & Ong, A. D. (2023). *Trajectories of affective well-being and survival in middle-aged and older adults*. https://osf.io/waf2m/?view_only=a32ddb5fa21543d1a8a966643e51e1c0

DeSteno, D., Gross, J. J., & Kubzansky, L. (2013). Affective science and health: The importance of emotion and emotion regulation. *Health Psychology*, *32*(5), 474–486. https://doi.org/10.1037/a0030259

Diallo, T. M. O., Morin, A. J. S., & Lu, H. (2016). Impact of misspecifications of the latent variance–covariance and residual matrices on the class enumeration accuracy of growth mixture models. *Structural Equation Modeling: A Multidisciplinary Journal*, *23*(4), 507–531. https://doi.org/10.1080/10705511.2016.1169188

Enders, C. K., & Bandalos, D. L. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal*, *8*(3), 430–457. https://doi.org/10.1207/S15328007SEM0803_5

Grimm, K. J., Ram, N., & Estabrook, R. (2016). *Growth modeling: Structural equation and multilevel modeling approaches*. Guilford Publications.

Guimond, A.-J., Trudel-Fitzgerald, C., Boehm, J. K., Qureshi, F., & Kubzansky, L. D. (2022). Is more, better? Relationships of multiple psychological well-being facets with cardiometabolic disease. *Health Psychology*, *41*(1), 32–42. https://doi.org/10.1037/hea0001154

Howard, M. C., & Hoffman, M. E. (2018). Variable-centered, person-centered, and person-specific approaches: Where theory meets the method. *Organizational Research Methods*, *21*(4), 846–876. https://doi.org/10.1177/1094428117744021

Joshanloo, M., & Bakhshi, A. (2016). The factor structure and measurement invariance of positive and negative affect. *European Journal of Psychological Assessment*, *32*(4), 265–272. https://doi.org/10.1027/1015-5759/a000252

Kazak, A. E. (2018). Editorial: Journal article reporting standards. *American Psychologist*, *73*(1), 1–2. https://doi.org/10.1037/amp0000263

Keyes, C. L. M. (1998). Social well-being. *Social Psychology Quarterly*, *61*(2), 121–140. https://doi.org/10.2307/2787065

Keyes, C. L. M. (2007). Promoting and protecting mental health as flourishing: A complementary strategy for improving national mental health. *American Psychologist*, *62*(2), 95–108. https://doi.org/10.1037/0003-066X.62.2.95

Kooken, J., McCoach, D. B., & Chafouleas, S. M. (2019). The impact and interpretation of modeling residual noninvariance in growth mixture models. *The Journal of Experimental Education*, *87*(2), 214–237. https://doi.org/10.1080/00220973.2017.1421516

Labouvie-Vief, G. (2003). Dynamic integration: Affect, cognition, and the self in adulthood. *Current Directions in Psychological Science*, *12*(6), 201–206. https://doi.org/10.1046/j.0963-7214.2003.01262.x

Laursen, B., & Hoff, E. (2006). Person-centered and variable-centered approaches to longitudinal data. *Merrill-Palmer Quarterly*, *52*(3), 377–389. https://doi.org/10.1353/mpq.2006.0029

Lim, H. J., Min, D. K., Thorpe, L., & Lee, C. H. (2017). Trajectories of life satisfaction and their predictors among Korean older adults. *BMC Geriatrics*, *17*(1), Article 89. https://doi.org/10.1186/s12877-017-0485-5

McCoach, D. B., & Cintron, D. (2022). *Introduction to modern modelling methods*. Sage.

McNeish, D., Peña, A., Vander Wyst, K. B., Ayers, S. L., Olson, M. L., & Shaibi, G. Q. (2023). Facilitating growth mixture model convergence in preventive interventions. *Prevention Science*, *24*(3), 505–516. https://doi.org/10.1007/s11121-021-01262-3

Mroczek, D. K., & Kolarz, C. M. (1998). The effect of age on positive and negative affect: A developmental perspective on happiness. *Journal of Personality and Social Psychology*, *75*(5), 1333–1349. https://doi.org/10.1037/0022-3514.75.5.1333

Muthén, L. K., & Muthén, B. O. (1998–2017). *Mplus user's guide* (8th ed.). https://www.statmodel.com/

Nagin, D. S., & Tremblay, R. E. (2005). Developmental trajectory groups: Fact or a useful statistical fiction? *Criminology*, *43*(4), 873–904. https://doi.org/10.1111/j.1745-9125.2005.00026.x

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396

Nylund-Gibson, K., & Choi, A. Y. (2018). Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science*, *4*(4), 440–461. https://doi.org/10.1037/tps0000176

Ong, A. D. (2010). Pathways linking positive emotion and health in later life. *Current Directions in Psychological Science*, *19*(6), 358–362. https://doi.org/10.1177/0963721410388805

Ong, A. D., & Steptoe, A. (2020). Association of positive affect instability with all-cause mortality in older adults in England. *JAMA Network Open*, *3*(7), Article e207725. https://doi.org/10.1001/jamanetworkopen.2020.7725

Pressman, S. D., & Cohen, S. (2005). Does positive affect influence health? *Psychological Bulletin*, *131*(6), 925–971. https://doi.org/10.1037/0033-2909.131.6.925

Pressman, S. D., Jenkins, B. N., & Moskowitz, J. T. (2019). Positive affect and health: What do we know and where next should we go? *Annual Review of Psychology*, *70*(1), 627–650. https://doi.org/10.1146/annurev-psych-010418-102955

Radler, B. T., Rigotti, A., & Ryff, C. D. (2018). Persistently high psychological well-being predicts better HDL cholesterol and triglyceride levels: Findings from the midlife in the U.S. (MIDUS) longitudinal study. *Lipids in Health and Disease*, *17*(1), Article 1. https://doi.org/10.1186/s12944-017-0646-8

Ram, N., & Grimm, K. J. (2009). Methods and measures: Growth mixture modeling: A method for identifying differences in longitudinal change among unobserved groups. *International Journal of Behavioral Development*, *33*(6), 565–576. https://doi.org/10.1177/0165025409343765

Reich, J. W., Zautra, A. J., & Davis, M. (2003). Dimensions of affect relationships: Models and their integrative implications. *Review of General Psychology*, *7*(1), 66–83. https://doi.org/10.1037/1089-2680.7.1.66

Ryff, C. D., Love, G. D., Essex, M. J., & Singer, B. (1998). Resilience in adulthood and later life. In J. Lomranz (Ed.), *Handbook of aging and mental health* (pp. 69–96). Springer.

Ryff, C. D., & Singer, B. (2000). Interpersonal flourishing: A positive health agenda for the new millennium. *Personality and Social Psychology Review*, *4*(1), 30–44. https://doi.org/10.1207/S15327957PSPR0401_4

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, *6*(2), 461–464. https://doi.org/10.1214/aos/1176344136

Steptoe, A. (2019). Happiness and health. *Annual Review of Public Health*, *40*(1), 339–359. https://doi.org/10.1146/annurev-publhealth-040218-044150

Steptoe, A., Gibson, E. L., Hamer, M., & Wardle, J. (2007). Neuroendocrine and cardiovascular correlates of positive affect measured by ecological momentary assessment and by questionnaire. *Psychoneuroendocrinology*, *32*(1), 56–64. https://doi.org/10.1016/j.psyneuen.2006.10.001

Steptoe, A., Wardle, J., & Marmot, M. (2005). Positive affect and health-related neuroendocrine, cardiovascular, and inflammatory processes. *Proceedings of the National Academy of Sciences*, *102*(18), 6508–6512. https://doi.org/10.1073/pnas.0409174102

Tein, J.-Y., Coxe, S., & Cham, H. (2013). Statistical power to detect the correct number of classes in latent profile analysis. *Structural Equation Modeling: A Multidisciplinary Journal*, *20*(4), 640–657. https://doi.org/10.1080/10705511.2013.824781

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis*, *18*(4), 450–469. https://doi.org/10.1093/pan/mpq025

Weiss, E. M., Gerstner, C.-C., McDermott, P. A., & Rovine, M. J. (2023). Latent trajectories of learning- and teacher-context behavior problems across the primary school transition. *Journal of Applied Developmental Psychology*, *86*, Article 101538. https://doi.org/10.1016/j.appdev.2023.101538

Wickrama, K., Lee, T. K., O'Neal, C. W., & Lorenz, F. (2021). *Higher-order growth curves and mixture modeling with Mplus: A practical guide* (2nd ed.). Routledge. https://doi.org/10.4324/9781003158769

Willroth, E. C., Ong, A. D., Graham, E. K., & Mroczek, D. K. (2020). Being happy and becoming happier as independent predictors of physical health and mortality. *Psychosomatic Medicine*, *82*(7), 650–657. https://doi.org/10.1097/PSY.0000000000000832

Zaninotto, P., Wardle, J., & Steptoe, A. (2016). Sustained enjoyment of life and mortality at older ages: Analysis of the English Longitudinal Study of ageing. *BMJ*, *355*, Article i6267. https://doi.org/10.1136/bmj.i6267

Received March 28, 2023
Revision received November 13, 2023
Accepted November 20, 2023 ■